DOCUMENT RESUME

ED 373 103 TM 021 998

AUTHOR	Kieras, David E.; Meyer, David E.
TITLE	The EPIC Architecture for Modeling Human Information-Processing and Performance: A Brief Introduction.
INSTITUTION	Michigan Univ., Ann Arbor. Div. of Research Development and Administration.
SPONS AGENCY	Office of Naval Research, Arlington, Va.
REPORT NO	TR-94/ONR-EPIC-1
PUB DATE	1 Apr 94
CONTRACT	N00014-92-J-1173
NOTE	22p.; For related document, see TM 021 997.
PUB TYPE	Reports - Evaluative/Feasibility (142)
EDRS PRICE	MF01/PC01 Plus Postage.
DESCRIPTORS	*Cognitive Processes; *Computers; *Interaction; Models; *Perceptual Motor Coordination; *Performance
IDENTIFIERS	*EPIC Architecture; Intertask Interference

ABSTRACT

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ED 373 103

Architecture for Real-Time Information-Processing Performance: A Brief Description

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EPIC Report No. 1 (TR-44/ONR-EPIC-1)

April 1, 1994

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

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1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	April 1, 1994	Interim Jan 1, 1992-April 1, 1994

4. TITLE AND SUBTITLE
The EPIC Architecture for Modeling Human Information-Processing and Performance: A Brief Introduction.

5. FUNDING NUMBERS
G N0014-92-J-1173
PR 4422574

6. AUTHOR(S)
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7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
University of Michigan
Division of Research development and administration
Ann Arbor, MI 48109-1274

8. PERFORMING ORGANIZATION REPORT NUMBER
TR-94/ONR-EPIC-1

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Cognitive Science Program (342 CS)
Office of Naval Research
800 N. Quincy St.
Arlington, VA 22217-5660

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for Public Release; Distribution Unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*

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14. SUBJECT TERMS	15. NUMBER OF PAGES
Human performance, Cognitive Models, Human-Computer Interaction	19+
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	

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ABSTRACT

EPIC (Executive Process-Interactive Control) is a human information-processing architecture that is especially suited for modeling multiple-task performance. The EPIC architecture includes peripheral sensory-motor processors surrounding a production-rule cognitive processor, and is being used to construct precise computational models for basic multiple-task situations. Some of these models are briefly illustrated here to demonstrate how EPIC applies to multiple-task performance, and helps clarify some basic properties of human performance. Additional applications of EPIC to modeling human-computer interaction are briefly summarized.

INTRODUCTION

This report is a brief introduction to the EPIC architecture for human information processing, which is being developed under ONR sponsorship. Additional reports now in preparation will provide considerably more detail on the architecture and its application to specific modeling domains in human multiple-task performance and human-computer interaction.

The goal of the EPIC project is to develop a comprehensive computational theory of multiple-task performance that (a) is based on current theory and results in cognitive psychology and human performance; (b) will support rigorous characterization and quantitative prediction of the mental workload and performance, especially in multiple-task situations; and (c) is useful in practical system design.

The orientation of the EPIC project toward practically useful prediction is important because proposals for cognitive theories that are indeed useful in practical system design are unusual. The best known previous attempt is the Model Human Processor (MHP) proposed by Card, Moran, and Newell (1983). The MHP is a remarkable synthesis of cognitive theory and empirical data based on the key insight that results from experimental psychology can be cast in the form of a simplified model with parametric properties. Such a model, if properly constructed, can serve as an *engineering model*, a model both simple and quantitatively accurate enough to be useful in the design of systems, such as computer user interfaces. The work of Gray, John, and Atwood

(1992) in which tasks are analyzed in terms of sequential and parallel MHP processes shows that this class of model can indeed be used for engineering analysis and design. However, our effort to construct computational models based on a more recent and more thorough examination of empirical results makes it clear that the MHP is both incomplete and incorrect in many significant respects.

EPIC was designed to explicitly couple the basic information processing and perceptual-motor mechanisms represented in the MHP with a cognitive analysis of procedural skill, namely that represented by production-system models such as Cognitive Complexity Theory (CCT, Bovair, Kieras, & Polson, 1990, ACT (Anderson, 1976), and SOAR (see Peck & John, 1992). Thus, EPIC has a production-rule cognitive processor surrounded by perceptual-motor peripherals; applying EPIC to a task situation requires specifying *both* the production-rule programming for the cognitive processor, and also the relevant perceptual and motor processing parameters.

The EPIC model is thus in same spirit as the MHP, but there are several key differences. First, relative to the MHP, we have used more recent and detailed empirical evidence, especially concerning multiple-task performance, to define the mechanisms in the EPIC architecture. The result is that all of the processors in EPIC have fundamental differences from those in the MHP; in particular, the motor processors are much more elaborated, and the cognitive processor is implemented as a production system whose rules represent how the system performs the task. Second, unlike the original MHP presentation, we have adopted a rigorous theoretical approach consisting of constructing and testing computational models and subjecting them to detailed quantitative comparison with data. Constructing such models involves a detailed task analysis of the experimental task, which is usually overlooked in conventional psychological theorizing, but is a key advantage of the computational model approach (see Kieras, 1990). Third, in comparison with the Gray, John, and Atwood (1992) models, our computational models are generative; that is, in the model, a simulated human with general procedural knowledge of the task interacts with a simulated task environment, and so the model generates the sequence of serial and parallel processes in the course of performing the task. Thus the task analysis reflected in the model is constrained to be general to a class of tasks, rather than reflecting specific task scenarios.

Much of our focus is on multiple-task performance, in which the human is trying to concurrently execute a set of tasks; the tasks are independent, in that each could be meaningfully described and conducted in isolation. A good example of a multiple-task situation is the airplane cockpit. In a multiple-task situation, the main problem confronting the human is to execute the independent tasks in a coordinated fashion that meets some constraints on overall performance, such as giving one task priority over the other. We have focused on multiple-task performance for two reasons: First, it is of great practical importance, but is theoretically underdeveloped. Second, the multiple-task situation stresses human capabilities very seriously, and so the patterns of experimental effects set very strong constraints on the human information-processing system architecture. Thus our analyses of even simple multiple-task situations have resulted in detailed hypotheses about human information processing mechanisms that are represented in the EPIC architecture.

THE EPIC ARCHITECTURE

System Structure and Principles

This is a preliminary report, so our presentation and justification of the architecture must be severely limited; a more detailed presentation appears in forthcoming reports, one that will provide a fully detailed view of the architecture, and another that will more completely describe the specific models presented below.

Figure 1 shows the overall structure of processors and memories in the EPIC architecture. At this level, EPIC is rather conventional, and closely resembles the MHP. However, there are some important new concepts in the EPIC architecture that this brief presentation will highlight.

As shown in Figure 1, there is a conventional flow of information from sense organs, through perceptual processors, to a cognitive processor (consisting of a production rule interpreter and a working memory), and finally to motor processors that control effector organs. Some new features relative to the older MHP proposal (Card, et. al, 1983) are as follows: There are separate perceptual processors with distinct processing time characteristics, and more motor processors, especially the ocular motor processor that controls where the eye is looking. There are feedback pathways from the motor processors, as well as tactile feedback from the effectors, which is important in coordinating multiple tasks. The declarative/procedural knowledge distinction of the "ACT-class" cognitive architectures (see Anderson, 1976) is represented in the form of separate permanent memories for production rules and declarative information. At this time, we do not propose specific properties of the working memory (WM) because clarifying what types of working memory systems are used in multiple-task performance is one of our research goals; in the meantime, WM contains all of the temporary information tested for and manipulated by the production rules, including control information such as task goals and sequencing information, and also conventional working memory items, such as representations of sensory inputs.

A single stimulus input to a perceptual processor can produce multiple outputs to be deposited in WM at different times. The first output is a representation that a perceptual event has been detected, followed later by a representation that describes the recognized event. For present purposes, we assume that the mean detection time is fixed, estimated at 100 ms for visual events and 50 ms for auditory, while the recoding process takes additional time after the detection process, and depends on the properties of the stimulus. For example, recognizing letters on screen in a typical experiment might take on the order of 150 ms after the detection time. At present, we have estimated these recognition times from the empirical data being modeled.

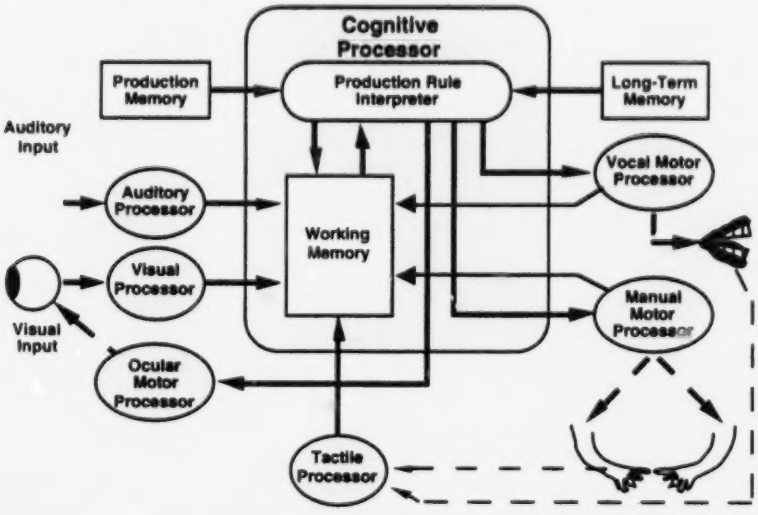

Figure 1. Overall structure of the EPIC architecture showing information flow paths as solid lines, mechanical control or connections as dotted lines.

The cognitive processor is programmed in terms of production rules, and so in order to model a task, we must supply a set of production rules that specify what actions in what situations must be performed to do the task. We are using the interpreter from the Parsimonious Production System (PPS) which is especially suited to task modeling work (see Bovair, Kieras, & Polson, 1990). One important feature of PPS is that control information such as the current goals is simply another type of WM item, and so can be manipulated by rule actions. A critical difference with the MHP is that on each cognitive processor cycle, any number of rules can fire and execute their actions; this parallelism is a fundamental feature of PPS. The cognitive processor accepts input only at the beginning of each cycle, and produces output at the end of the cycle, whose mean duration we estimate at 50 ms. Thus, unlike the MHP, the EPIC cognitive processor is not constrained to be doing only one thing at time. Rather, multiple processing threads can be represented simply as sets of rules that happen to run simultaneously.

An important difference with the MHP involves the basic temporal relationships of the processors. The perceptual processors in EPIC are "pipelines," in that an input produces an output at a certain later time, independently of what particular time it arrives. However, the cognitive processor accepts input only every 50 ms, and is constantly running, not synchronized with external events. This means that perceptual processor output to the cognitive processor must wait an average of 25 ms until it is accepted. Thus the temporal resolution on sensory events is limited centrally, rather than reflecting temporal integration by the perceptual processors, as proposed in the MHP. Our proposal, along with the 50 ms cognitive cycle time, is supported nicely by work on human simultaneity judgments (Kristofferson, 1967).

The EPIC motor processors are much more elaborate than those in the MHP. Certain results (e.g., McLeod, 1977) motivate our assumptions that the motor processors operate independently, but the hands are bottlenecked through a single manual processor. Thus, the hands normally cannot be controlled independently; rather they can be operated either one at a time, or synchronized with each other. Current research on movement control (e.g., Rosenbaum, 1980) suggests that movements are specified in terms of features, and the time to produce a movement depends on its feature structure as well as its mechanical properties. We have represented this property in highly simplified models for the motor processors. The input to the motor processors consist of a symbolic name for the desired movement, or movement feature. The processor recodes the symbol into a set of movement features, and then initiates the movement. The external device will then detect the movement after some additional mechanical delay. For example, using our estimates, if the desired movement is to press a button with the right-hand index finger, the symbolic name would be recoded into the movement features <RIGHT, INDEX>, taking an average of 50 ms each, followed by 50 ms for the movement initiation, and a final 10 ms for the mechanical motion of pressing the button.

An important empirical result is that effectors can be preprogrammed if the movement can be anticipated (Rosenbaum, 1980). In our model, this takes the form of instructing the motor processor to generate the features, and then at a later time instructing the movement to be initiated. As a result of the pre-generation of the features, the resulting movement will be made sooner.

We simulate task performance by simulating the human interacting with the task environment in simulated real time, in which the processors run independently and in parallel. We include a process that represents the task, and which generates stimuli and collects the responses and their simulated times over a large number of trials. To represent human variability, the processor time parameters are varied stochastically about their mean values with a regime that produces a coefficient of variation for simple reaction time of about 20%, which is a typical empirical value.

A Comparison of EPIC with MHP

The similarities and differences between EPIC and the MHP can be illustrated by how the two architectures produce approximately the same prediction of the time for a simple reaction task. In the simple reaction task, the subject simply makes a response (e.g. pushing a button with the index finger) when a stimulus appears (e.g. a single light comes on), where there is only one possible stimulus and response. For both architectures, it takes 100 ms to detect the stimulus; in a simple reaction time task, it is not necessary to recognize or recode the stimulus before making a response, which would take longer in the EPIC architecture. Both architectures would require only a single cognitive cycle to select the response to the stimulus. The MHP assumes that a cycle is nominally 70 ms; in EPIC, the perceptual output must wait an average of 25 ms before being accepted by the cognitive processor, and then it takes 50 ms for the cognitive cycle to complete, for a mean total of 75. The MHP would require only a single motor cycle of 70 ms to produce the response; in EPIC, because the response in a simple reaction task can be prespecified, the movement features can be generated in advance, and only the movement initiation time of 50 ms followed by the mechanical time, estimated at 10 ms, is required for making the response, for a total of 60 ms. Thus the MHP requires a total of 100+70+70=240 ms for a simple reaction; the EPIC architecture requires the essentially identical 100+75+60=235 ms.

Of course with more complex tasks and strategies, the two architectures will not look so similar. The differences begin to appear even for the very simplest choice reaction or tracking tasks. In fact, the two architectures are not really comparable for complex tasks and situations because fundamentally different mechanisms come into play. For example, the MHP does not include a motor feature mechanism, nor differential times for auditory vs. visual detection and recognition times. More importantly, in EPIC the cognitive processor must be explicitly programmed with production rules in a specified format; this property of the MHP is only suggested in Card, Moran, & Newell (1983). Thus, while similar in structure and spirit to the MHP, the EPIC framework operates at a much more detailed and specific level of analysis, and with a explicit computational representation of the task.

Rationale for EPIC's Basic Assumptions

The literature on multiple-task performance is extensive, and will not be summarized here. (for a review, see Gopher & Donchin, 1986). Of course human information processing is limited in capacity, and it has been traditionally assumed that there is a single-channel bottleneck (Welford, 1952). But humans can do multiple tasks, sometimes impressively well, and their ability to do so depends strongly on the specific combinations of tasks involved. The multiple-resource theory (Wickens, 1984) is an attempt to summarize these relationships. They pose a fundamental theoretical dilemma of how to reconcile the complex patterns of multitasking abilities with some notion that the overall capacity of the human system is limited.

In developing EPIC, our theoretical strategy is to make a radical assumption and then explore its consequences through modeling. We assume that all capacity limitations are a result of limited structural resources, rather than a limited cognitive processor. Thus, the EPIC cognitive processor can fire any number of rules simultaneously, but since the peripheral sense organs and effectors are structurally limited, the overall system is sharply limited in capacity. For example, the eyes can only fixate on one place at a time, and the two hands are bottlenecked through a single processor. We also assume that certain apparent limitations in central capacity arise when modality-specific working memories must be used to maintain task information, but we have not yet tested this assumption in the EPIC framework. Thus far, this simple and radical set of assumptions about the nature of multiple-task processing limitations has held up well.

Multiple Tasks and Executive Processes

Some theories of multiple-task performance postulate an executive control process that coordinates the separate multiple tasks (e.g. Norman & Shallice, 1986). We do likewise, but a key feature of our approach is that the executive control process is just another set of production rules. These rules can control other task processes by manipulating information in WM. For example, we assume that each task is represented by a set of production rules that have the task goal appearing in their conditions, and so an executive process rule can suspend a task by removing its governing goal from WM, and then cause it to resume operation by reinserting the goal in WM. Also, the executive process can cause a task to follow a different strategy by placing in WM an item which task rules test for, thus enabling one set of rules, and disabling another. In addition, the executive process may control sensory and motor peripherals directly, such as moving the eye fixation from one point to another, in order to allocate these resources between two tasks. Thus, rather than postulating an executive control mechanism that is somehow different in kind than other cognitive mechanisms, EPIC has a uniform mechanism for the control of behavior, both at the executive level and at the detailed level of individual task actions. As a corollary, learning how to coordinate multiple tasks is simply learning another (possibly difficult) skill, as has been proposed by some recent investigators (Gopher, 1992).

ILLUSTRATION OF EPIC MODELS FOR MULTIPLE TASKS

A Basic Multiple-Task Paradigm

In order to illustrate how EPIC permits us to investigate multiple-task performance in detail, some illustrative results will be presented for one basic, and heavily researched, dual-task situation. In this situation, the subject performs two simple stimulus-response tasks in succession as shown in Figure 2. The two tasks are usually choice reaction tasks, such as pressing one of two keys depending on which of two letters appear, and then making one of two vocal responses depending on whether a high or low frequency tone is heard. The stimuli for the two tasks appear in succession, and the time delay between the two stimuli is manipulated, typically over a range of 0-1000 ms. The subject is typically instructed to give priority to Task 1 (Stimulus 1) over Task 2 by making Response 1 before Response 2, and to make the responses as fast as possible within this constraint. This situation has been extensively studied, and there is an important effect that appears in it, the Psychological Refractory Period (PRP) effect (for thorough reviews, see Bartelson, 1966; Kantowitz, 1974; Pashler, 1990).

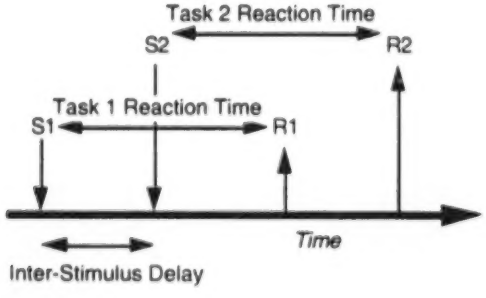

Figure 2. The PRP paradigm. Stimulus 2 is presented with a delay after Stimulus 1, and the time taken to respond to each stimulus is measured.

The PRP effect is that the Task 2 reaction time increases by a substantial amount (hundreds of milliseconds) if Stimulus 2 appears soon after Stimulus 1, and drops to a baseline level if the delay is long enough (see observed curves in Figures 3 and 4). While it is easy to see how this effect would result if the two tasks had to share perceptual or motor processors, the PRP effect occurs even when different stimulus and response modalities are used in the two tasks. In fact, various results show that if the stimuli are in different modalities, the perceptual processing can be done simultaneously for the two tasks (Pashler, 1984).

Demonstration of Parallel Cognitive Processing in Multiple Tasks

The traditional explanation for the PRP effect assumes that the cognitive processor can do only one thing at a time, so the cognitive process of selecting the response for Stimulus 2 must be delayed until Response 1 has been selected or executed. However, results from our quantitative computational model have led us to conclude that response selection can also be done for both tasks simultaneously, meaning that the cognitive processor fires response selection rules in parallel. Here we will present EPIC models for both explanations. In both cases, in order to ensure that the response to Stimulus 1 is always made first, the executive process must delay some aspect of Task 2 until Task 1 is complete. The two explanations differ in which process is postponed: response selection (the traditional explanation) or response production.

We have modeled a data set collected by Hawkins, Rodriguez, and Richer (1979), who conducted one of the most precise and comprehensive PRP studies available. The independent variables included the stimulus and response modalities for the choice reaction tasks and also the difficulty of the second task. Figure 3 shows the observed Task 2 reaction times when the Stimulus 1 is auditory and Response 1 is a left-hand manual button press, and the Stimulus 2 is visual and Response 2 is also a manual button press, but using the right hand.

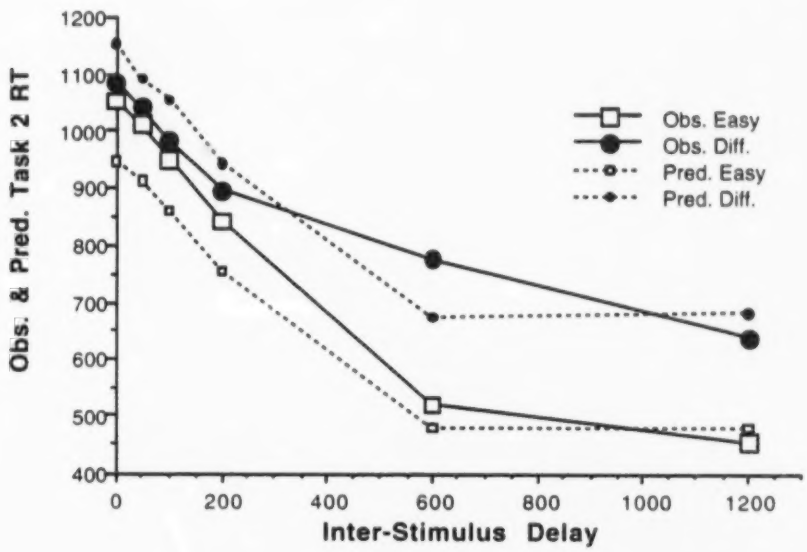

Figure 3. Selection-postponement model: Observed and Predicted Task 2 Reaction Time (RT) for Auditory-Manual Task 1 at two difficulty levels. Easy Task 2 is square points and takes less time than Difficult, shown as circular points. Observed data are large points with solid lines; predicted values are small points with dotted lines.

Considering for the moment just the observed data at long delays, the lower curve is for Task 2 being Easy (a 2-2 stimulus-response mapping); the upper curve is for Task 2 being Difficult (an 8-2 mapping). The Difficult Task 2 takes longer because on the average, more cognitive processor cycles are required to select the response.

Consider first an EPIC model based on the conventional assumption that the cognitive processor can select only one response at a time. The predicted values shown in Figure 3 were obtained with such a *selection-postponement* model. Figure 4 shows a flowchart for the model processing. At the beginning of the trial, the executive process suspends the Task 2 response selection rules by removing the Task 2 goal from WM, and replaces it when the Task 1 response has been made, ensuring that Response 2 will be selected and produced after Response 1. At short delays, Task 2 must wait for the Task 1 response, but at long delays, Task 2 is free to run as soon as Stimulus 2 arrives because Task 1 is complete; thus as shown in Figure 3, the model predicts an overall PRP effect; the Task 2 reaction time is much slower at smaller inter-stimulus delays.

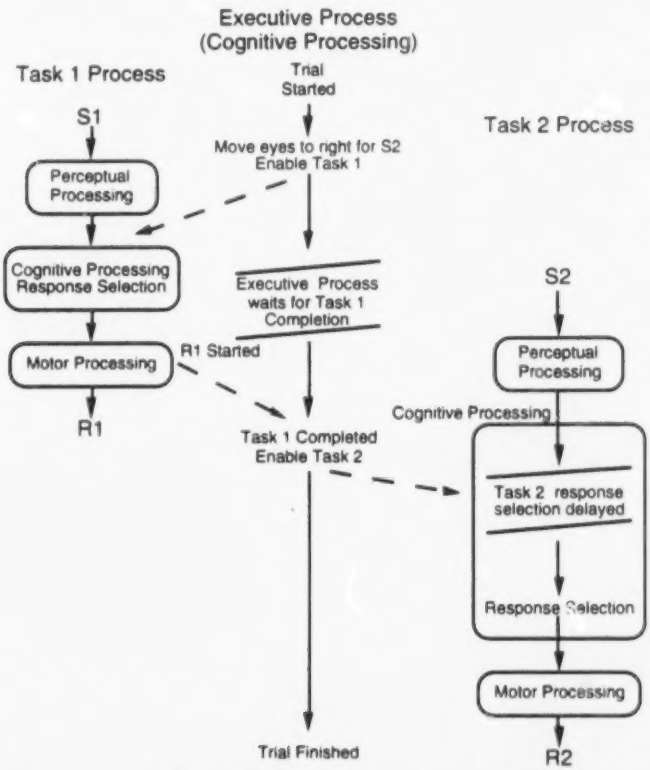

Figure 4. Selection-postponement model: The executive process enables Task 1 response selection processing but does not enable Task 2 response selection until Task 1 is complete.

However, there is a serious misfit in Figure 3. Note how the effect in the data of Task 2 difficulty is much smaller at short delays than at long delays. In contrast, the selection-postponement model predicts that the effect of Task 2 difficulty should be the same at both short and long delays, because Task 2 response selection is always postponed until Task 1 is complete. Such models cannot explain this differential effect of difficulty.

Now consider an EPIC model that takes advantage of the parallel operation of the cognitive processor by postponing response production instead of response selection. The flowchart for this

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response-postponement model is shown in Figure 5. The executive process allows Task 2 response selection to go on until a response is selected, but then requires Task 2 to wait for permission to instruct the motor processor to produce the response. After Response 1 has been made, the executive permits Task 2 to send the response information to the motor processor. Figure 6 shows the predicted values for the same data generated by this response-postponement model. Because the Task 2 response selection rules can fire in parallel with the Task 1 rules, the Difficult task does not take much more time than the Easy task at short delays; both perceptual and cognitive processing for the two tasks can be substantially overlapped. However, at long delays there is no overlap, and so the full time for each processor to complete its work shows up in the Task 2 reaction time.

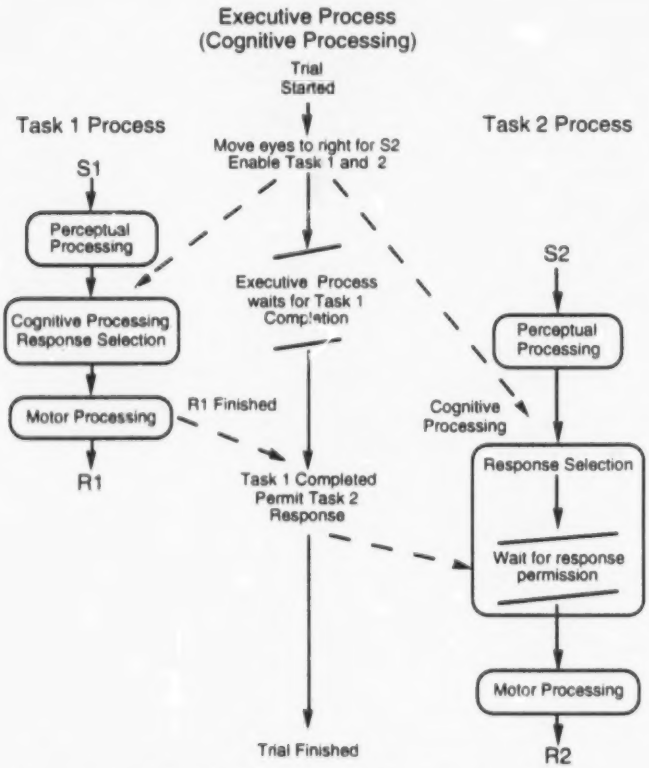
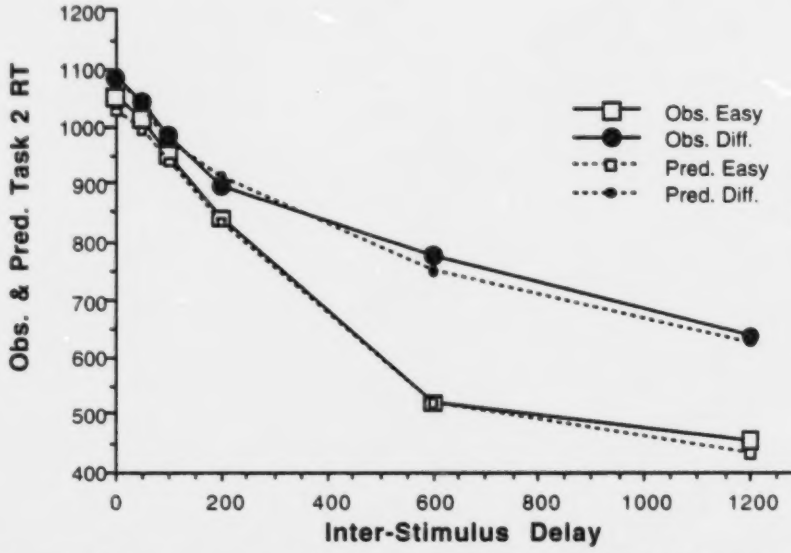


Figure 5. Response-postponement model: The executive process enables response selection processing for both Task 1 and Task 2, but does not allow Task 2 to instruct the motor processor until Task 1 is complete.

The better fits in Figure 6 compared to Figure 3 are also due to two additional mechanisms. First, if Task 1 is complete when Stimulus 2 arrives, then Task 2 can be done in a different mode, in which the response can be sent directly to the motor processor, saving some time. Second, if there is adequate delay between Task 1 and Task 2, the manual motor processor can be preprogrammed with the right-hand feature for Response 2, thereby speeding up the response production. The good fit of this model to the data is typical of our models of PRP data.

To account for the Hawkins *et al.* data set, we propose a different executive process strategy for each of the four combinations of stimulus and response modalities used in the study. Because the subjects were very well practiced, it seems reasonable that the executive strategies will minimize response time as much as possible, and the executive strategies thus depend on the modality combination. For example, if both stimuli are visual, the executive process moves the eye from the

site of the first stimulus when it is detected to the second stimulus, while allowing both tasks to run to completion as soon as they receive their input without postponement or other overhead. This is optimal because the eye movement delay is long enough to ensure that the responses appear in the correct order. The resulting set of four executive models, running with identical rule sets for the two tasks, accounts for almost all of the systematic variance among the mean Task 2 reaction times across inter-stimulus delays, stimulus modalities, and response modalities, having $r^2 = .99$, $N = 48$ (see Meyer & Kieras (1994), for a discussion of the details of these results and the issues of goodness-of-fit and degrees of freedom).



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Current Work on a Classic Multiple-Task Paradigm

Another model under development concerns a very heavily studied multiple-task paradigm in which the subject must perform both a tracking task and a choice task. Developing an EPIC model for tracking brings out many key issues about the nature of tracking; our approach has been to represent tracking as a distinct motor processor "style" in which the human has a well-learned skill for operator the tracking control; the cognitive processor need only supervise the process. Our current work is modeling some results obtained by Martin-Emerson and Wickens(1992) which are especially revealing about the role of eye movements and the use of visual information during such a dual task.

APPLICATION OF EPIC TO HUMAN-COMPUTER INTERACTION

Comparison to Other Models of Human-Computer Interaction

Since it is a general model of human information processing and performance, EPIC should be applicable to many issues in human-computer interaction (HCI). In fact it incorporates and extends some of the most successful theoretical concepts in HCI.

Production-rule models, and their higher-level relative, GOMS models (Card, Moran, & Newell, 1983; Kieras, 1988), appear to capture the procedural requirements of an interface very well. In the Cognitive Complexity Theory (CCT) approach (Kieras & Polson, 1985; Bovair, Kieras, & Polson, 1990), the production rules are organized in a GOMS format, being organized hierarchically and sequentially by goals and methods. But models at the level of the MHP appear to capture very well the processing sequence characteristics of a task. For example, the scheduling-chart models in Gray, John, and Atwood (1992) for telephone operator tasks show which processor runs at what time, and which waits for output from another. This seems to be a useful characterization for tasks such as telephone operator tasks, because the sequence of processing would be optimized for speed and stable for such well-practiced, time-critical tasks. Since both CCT and MHP models seem to be successful in their domains, it is important to see how they both fit into a framework such as EPIC.

The CCT production-rule models can be mapped to the EPIC architecture in that the CCT model production rules are simply executed as-is by the cognitive processor. The perceptual and motor operators "bypassed" in the CCT analysis would be lower-level methods that interact closely with the perceptual and motor processors, as would be involved, for example, in visually locating an object on the screen. If the quality of the interface depends heavily on such perceptual-motor interactions, then an EPIC model should be more exact and useful than a CCT model.

The Gray et al. scheduling-chart models for the telephone operator tasks relate to EPIC in that they show the sequence and relations of the processor activities, but the method followed by the human in doing the task is implicit, rather than explicit, in the schedule chart. So analyzing one of these tasks with EPIC requires writing the production rules to be followed by the cognitive processor in performing the task, ensuring for example, that eye movements are made at the proper time. Such a model can then generate behavioral predictions for any instance of the task. The explicit production-rule representation also facilitates comparison of the structure of different tasks.

A High-Performance Human-Computer Interaction Task

We are developing EPIC models for the telephone operator tasks studied by Gray, John, and Atwood (1992). These tasks are of special interest because an analysis of them in terms of the MHP was of considerable economic value in this domain where a second's difference in average task completion time is worth a substantial amount of money. The EPIC architecture is "programmed" with a set of production rules capable of performing all possible instances of the telephone operator tasks that are within the scope of the rules. The perceptual and motor processors generate the times required to move the eyes around, perceive stimuli on the operator's workstation screen, and reach for and strike keys under the direction of the cognitive processor rules. These rules can arrange to overlap some of the activities in order to save time. These EPIC models for the telephone operator tasks are similar to our PRP task executive models, in that they are optimized for speed by overlapping as many processes as possible, and by preparing or executing motor movements as soon as the task permits. Such optimized rules are organized according to the optimal temporal interleaving of the peripheral processes, analogous in organization to highly speed-optimized code for a real-time computer system.

In preliminary results, the EPIC models appear capable of generating usefully accurate predicted completion time for such tasks rather more easily and generally than the MHP-based analyses. This

work has been presented in Wood, Kieras, and Meyer (1994).

Representation of Skill in HCI Tasks

In high-performance tasks such as the telephone operator tasks, and indeed many multiple-task situations, it is critical for the human operator to act as rapidly as possible. Constructing models for such tasks in EPIC allows us to explore how such procedural skill would be represented, and how it might develop. Based on existing research, representing procedural knowledge as structured in terms of a hierarchy of goals and methods, as in the GOMS model, appears to be both theoretical appealing and empirical accurate, at least in many task domains such as text editing. Such a representation is analogous to well-modularized code in the structured programming style. Furthermore, if the interface can be operated with a simple and consistent set of methods, then it is relatively fast to learn. Thus procedures that are well-structured in GOMS terms should correspond to easily learned interfaces.

However, a disadvantage of such GOMS-structured procedural knowledge is that, as represented in EPIC, there is a certain amount of overhead in processing the hierarchically structured procedural knowledge, analogous to the subroutine calling overhead in computer programs. Thus GOMS-structured procedures may be inherently slower than less well-structured representations.

But there is an additional speed disadvantage of GOMS-structured methods: they are committed to executing only in the context of accomplishing the current goal. In contrast, our EPIC models can, when appropriate, take advantage of certain possibilities for speeding up execution that involve making actions early, and out of their apparent procedural context, such as starting an eye movement during one part of the task in anticipation of getting information needed in a later part of the task. Such anticipatory actions are not contained strictly in the goal-based methods to which they are relevant. This approach to organizing actions violates a principle of modularization in good computer programming practice, in which the computations relevant to particular programming goal are kept together, encapsulated in their own distinct routines. Thus the greater speed is had at the expense of the modular goal-organized procedures.

Yet EPIC is not rigidly committed to either GOMS-structured production rules, or speed-optimized production rules. Rather, using EPIC brings out the important puzzle of when the production rules in a model would be GOMS-structured versus optimized for speed. Perhaps the production rules for time-stressed highly practiced skills would be in the speed-optimized form, while normal, less-practiced skills would be GOMS-structured. Learning a procedural skill might progress from the initial stages to a fully automated, or "tuned" state by changes in the production-rule organization (see Anderson, 1987; Card, Moran, & Newell, 1983; Schneider, 1985). When the system is first learned, a GOMS representation of the skill seems reasonable, in that the user's procedural knowledge is organized in terms of methods for accomplishing goals, and these methods are executed in a sequential hierarchical fashion, especially if speed is not critical or the perceptual and motor activities must be done sequentially. These methods could be refined to some extent with further practice (Bovair, Kieras, & Polson, 1990). But after extreme practice, especially if speed of operation is critical and perceptual and motor activities can be done simultaneously, the methods may become "flattened" and interleaved, so the original goal-hierarchical sequential form is lost in favor of a representation that permits the fastest possible temporal coordination of the processes with minimal cognitive activity.

The interesting question this analysis brings out concerns the extent to which there is some form of tradeoff between whether an interface would be easily learned by virtue of having a good GOMS structure versus it being easily speed-optimized by virtue of having a structure that permits time-consuming actions to be interleaved and overlapped. If we understood the relationship between well-modularized and speed-optimized procedures, we could determine whether an interface design can support an extreme level of skill by determining whether it would be possible for speed-optimized procedures to be derived from the initial GOMS-structured procedures. For example, compared to a system that will always be operated according to sequential methods for hierarchical goals, a system

that must eventually be operated at very high speed will not only have to meet more stringent requirements on display design and input devices, it might also require very specific sequences of display events and input operations. For example, one of the workstations analyzed in Gray, John, and Atwood (1992) was unnecessarily slow because one input operation could not be overlapped with other processes.

CONCLUSION

The PRP and HCI models summarized here illustrate how the EPIC framework can represent a task situation in quantitative detail, and can address some fundamental issues about the cognitive architecture and how multiple tasks are coordinated. One result is that a central bottleneck is not a necessary assumption, and that data thought to require such an assumption can be explained by more obvious competition for the same peripherals in the context of the requirements of the task. The role of the executive process as a coordinator and sequencer of task performance is made clear. The executive strategies attempt to optimize the task performance by sequencing the activities of the peripheral processors based on their temporal characteristics.

The potential for EPIC to function as an engineering model in practical domains such as computer user interface design is clear from our current work with telephone operator tasks. In addition, by developing and applying an explicit theoretical framework, it is possible to explore otherwise unrealized and intractable theoretical issues. For example, our current work on tracking tasks has brought out many poorly understood aspects of the tracking task. Another insight comes from the above discussion about the representation of skill, which points to a hitherto unrealized twist on the ease-of-learning/speed-of-use distinction and the relation between interfaces for desktop and office tasks and those for supporting high-performance tasks.

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